# Optimization notes

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# Directional derivative

From a starting point $\underline{x}_0$ and a given dirction $\underline{u}$:

- $\underline{x}(\lambda) = \underline{x}_0 + \lambda \underline{u}$
  - $\lambda$ is a scalar.
- $d\underline{x} = \underline{u} d\lambda$
  - For a small change in $\lambda$.
- $F(\lambda) = f(\underline{x}_0 + \lambda \underline{u})$

$$\begin{aligned} dF = df &= (\nabla f(\underline{x}))^\top d\underline{x} \\ &= (\nabla f(\underline{x}))^\top \underline{u} d\lambda = \nabla^\top f \underline{u} \lambda \end{aligned}$$

- $\frac{df}{d\lambda} = \nabla^\top f \underline{u}$
  - If $f$ is minimized at $\underline{x}^* = \underline{x}_0 + \lambda \underline{u}$, then:
    - $\nabla f(\underline{x}^*))^\top f \underline{u} = 0$
    - gradient $f$ evaluated at the minimum point is orthogonalto $\underline{u}$.

## Weierstrass Theorem

If $f(\underline{x})$ is continuous on a nonempty feasible set that is cloased and bounded, then $f(\underline{x})$ has a global minimum in this set.

- A set $S$ is bounded if for any point $\underline{x}$ in $S$, we have $\underline{x}^\top \underline{x} < c$
  - $c$ is a finite positive number.

# Single-variable unconstrained optimization

- Necessary condition
  - If a function $f(x)$ has a local minimum at $x = x^*$, and $f'(x)$ exists as a finite number at $x = x^*$, then $f'(x^*) = 0$.
  - $x^*$ at $f'(x^*) = 0$ is called stationary point.
- Sufficient condition
  - Suppose $f'(x^*) = f''(x^*) = \cdots = f^{(m-1)}(x^*) = 0$, but $f^{(m)}(x^*) \neq 0$, then $f(x^*)$ is:
    - 1. a local minimum if $f^{(m-1)}(x^*) > 0$ and $m$ is even.
    - 2. a local maximum if $f^{(m-1)}(x^*) < 0$ and $m$ is even.
    - 3. neither a maximum nor a minimum if $m$ is odd.

# Multi-variable unconstrained optimization (1)

Definition of $r^{th}$ differential of function $f$:

$$d^r f(\underline{x}^*) = \sum_{i=1}^{n} \sum_{j=1}^{n} \cdots \sum_{k=1}^{n} h_i h_j \ldots h_k \frac{\partial^r f(\underline{x}^*)}{\partial x_i \partial x_j \ldots \partial x_k}$$

**Example**

When (order) $r = 2$ and (number of variables) $n = 3$, we have:

$$\begin{aligned}
d^2 f(\underline{x}^*) = d^2 f(x_1^*, x_2^*, x_3^*) &= \sum_{i=1}^{3} \sum_{j=1}^{3} h_i h_j \frac{\partial^2 f(\underline{x}^*)}{\partial x_i \partial x_j} \\
&= h_1^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1^2} + h_2^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_2^2} + h_3^2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_3^2} \\
&+ 2h_1 h_2 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1 \partial x_2} + 2h_2 h_3 \frac{\partial^2 f(\underline{x}^*)}{\partial x_2 \partial x_3} + 2h_1 h_3 \frac{\partial^2 f(\underline{x}^*)}{\partial x_1 \partial x_3}
\end{aligned}$$

# Multi-variable unconstrained optimization (2)

- Necessary condition

$$\frac{\partial f(\underline{x}^*)}{\partial x_1} = \frac{\partial f(\underline{x}^*)}{\partial x_2} = \cdots = \frac{\partial f(\underline{x}^*)}{\partial x_n} = 0$$

  - In vector form, $\nabla f(\underline{x}^* = 0)$.
  - $\underline{x}^*$ at $\nabla f(\underline{x}^* = 0)$ is called stationary point.
- Sufficient condition
  - For a stationary point at $\underline{x} = \underline{x}^*$:
    - if the Hessian matrix of $f(\underline{x})$ evaluated at $\underline{x} = \underline{x}^*$ is positive definite, then $\underline{x}^*$ is a local minimum.
    - if the Hessian matrix of $f(\underline{x})$ evaluated at $\underline{x} = \underline{x}^*$ is negative definite, then $\underline{x}^*$ is a local maximum.

# Hessian Matrix

- $(H_f)_{i,j} = \frac{\partial^2 f}{\partial x_i \partial x_n}$
- In matrix form: $H_f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$

# Definiteness

- A matrix is positive definite if all its eigenvalues are positive.
  - If some of the eigenvalues are positive and some are zero, then the matrix is positive semidefinite.
- Checking the sign of the determinants is an alternative way to determine the definiteness of a matrix.
- A twice differentiable function is convex if and only if its Hessian matrix is positive semi-definite.
  - The function is strictly convex if the Hessian matrix is positive definite.

# Multivariable optimization with equality constraints

**Lagrange Multiplier Theorem**

- Suppose the point $\underline{x}^*$ minimizes $f(\underline{x})$ and satisfies the equality constraints: $h_j(\underline{x}^*) = 0$, for $j = 1, 2, \ldots, m$
- Assume that the constraint gradients $\nabla h_j(\underline{x}^*)$ are linealy independent.
- Then there exists a unique set $\lambda_j^*$ $(j = 1, 2, \ldots, m)$ satisfying:

$$\frac{\partial L}{\partial x_i} = \frac{\partial f}{\partial x_i} + \sum_{j=1}^{m} \lambda_j^* \frac{\partial h_j}{\partial x_i} = 0$$

where $i = 1, 2, \ldots, n$.

# Simplex method: Introduction

**Definition of Simplex**

The geometric figure formed by a set of n + 1 points in an n-dimensional space is called a simplex.

- When the points are equidistant, the simplex is said to be *regular*.
- In two dimensions the simplex is a triangle, and in three dimensions, it is a tetrahedron.
- The simplex method was originally given by Spendley et al. and was developed later by Nelder and Mead.

# Simplex method: Steps

Choose a reflection coefficient $\alpha > 0$, an expansion coefficient $\gamma > 1$, and a contraction coefficient $0 < \beta < 1$.

1. Identify $\underline{x}_{\text{min}}$ and $\underline{x}_{\text{max}}$ amoung $\{\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_{n+1}\}$
   - such that $f(\underline{x}_{\text{min}})$ is the minimum and $f(\underline{x}_{\text{max}})$ is the maximum of all the $f(\underline{x}_i)$, for $i = 1, 2, \ldots, n+1$.
   - If $|\underline{x}_{\text{max}} - \underline{x}_{\text{min}}| < \epsilon$, stop. The minimum is at $\underline{x}_{\text{min}}$.
   - Otherwise, let $\underline{x}_a$ be the averaged position of $\{x_1, x_2, \ldots, x_{n+1}\}$, excluding $\underline{x}_{\text{max}}$, and go to step 2.
2. Let the reflection point $\underline{x}_r = \underline{x}_a + \alpha(\underline{x}_a - \underline{x}_{\text{max}})$.
   - If $f(\underline{x}_{min}) > f(\underline{x}_r)$, let the expansion point $\underline{x}_e = \underline{x}_a + \gamma(\underline{x}_r - \underline{x}_a)$, and go to step 3.
   - Otherwise, go to step 4.

# Simplex method: Steps

3. If $f(\underline{x}_r) > f(\underline{x}_e)$, the point $\underline{x}_{\max}$ is replaced by $\underline{x}_e$.
    - Otherwise, $\underline{x}_{\max}$ is replaced by $\underline{x}_r$. A new set of n+1 points is formed. Then go to step 1.
4. If the second largest $f(\underline{x}_i) > f(\underline{x}_r)$, then $\underline{x}_{\max}$ is replaced by $\underline{x}_r$ to form a new set of n+1 points, and go to step 1.
    - Otherwise, go to step 5.
5. Let $\underline{x}_p$ be defined such that $f(\underline{x}_p) = \min\{f(\underline{x}_r), f(\underline{x}_{\max})\}$ and let the contraction point $\underline{x}_c = \underline{x}_a + \beta(\underline{x}_p - \underline{x}_a)$.
    - If $f(\underline{x}_c) > f(\underline{x}_p)$, replace $\underline{x}_j$ by $\underline{x}_j + (\underline{x}_{\min} - \underline{x}_j)/2$, for $j = 1, 2, \ldots, n+1$, and go to step 1.
    - Otherwise, $\underline{x}_c$ replaces $\underline{x}_{\max}$ to form a new set of n+1 points, and go to step 1.